throughout a 52-week long follow-up. After constructing panels of variables based on knowledge, we employed ML to develop predictive models utilising the least absolute shrinkage and selection operator (LASSO) and logistic regression. A stratified split was applied to partition the study population into a training (70%; N=2547), and a test set (30%; N=1091). The training set was used in model development while the internal validation was developed by a 10-fold cross validation. The test set was used for validating the built model.

Results A total of 105 SLE patients (2.89%) experienced a neuropsychiatric flare during follow-up. Knowledge-driven feature selection included a history of NPSLE, disease duration, anticardiolipin positivity, clinical Systemic Lupus Erythematosus Disease Activity Index 2000 (SLEDAI-2K), sex, age, and the use of antimalarials. Both classifiers demonstrated comparable performance, with an AUC of 0.80 and 0.80, sensitivity of 0.61 and 0.61, and specificity of 0.83 and 0.82, respectively.

Conclusions The integration of traditional risk factors for NPSLE into ML-based models can predict neuropsychiatric involvement in SLE with high specificity and modest sensitivity. We herein propose a pragmatic, robust, and highly accurate prediction tool forecasting neuropsychiatric flares in SLE patients. The utilisation of this ML-based tool holds promising prospects for improving patient care and outcomes in real-world settings.

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P62 MACHINE LEARNING APPROACHES FOR PREDICTION OF RENAL FLARES IN SYSTEMIC LUPUS ERYTHEMATOSUS: KNOWLEDGE-DRIVEN MODELS OUTPERFORMED DATA-DRIVEN MODELS

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Objective Renal flares in patients with systemic lupus erythematosus (SLE) result in significant nephron loss. Thus, identification of reliable early signals of impending renal flares is anticipated to improve the prognosis for these patients. In this study, we implemented two different approaches of machine learning (ML) algorithms to identify baseline clinical determinants of renal flare occurrence in a large cohort of SLE.

Methods We analysed data from five phase III trials (BLISS-52, BLISS-76, BLISS-NEA, BLISS-SC, EMBRACE) after excluding patients with baseline British Isles Lupus Assessment Group (BILAG) A or B (N=3169). Renal flare was defined as a change from C, D, or E to A or B in the renal domain of the classic BILAG index within a 52-week long follow-up. Following construction of panels of variables using either (i) knowledge or (ii) feature selection methods, we developed ML classifiers including extreme gradient boosting (XGBoost), least absolute shrinkage and selection operator (LASSO), random forest (RF), and logistic regression. A stratified split was applied to partition the study population into a training (90%; N=2853) and a test set (10%; N=316). The training set was used in model development while the internal validation was developed by 10-fold cross validation. The test set was used for validation of the built model. Both approaches yielded final models that utilised the minimal number of features while maintaining optimal performance.

Results Of 3169 patients, 899 (28.3%) developed a renal flare during follow-up. XGBoost yielded the greatest accuracy both in the hypothesis-driven (0.97) and data-driven approach (0.88), as well as the highest performance metrics (AUC: 0.97 and 0.91; sensitivity: 1.00 and 0.82; specificity: 0.94 and 0.94, respectively) and an adequate calibration on the test dataset. The final model successfully reduced the number of features to five: renal BILAG C or D, urine protein creatinine ratio, serum albumin, blood urea nitrogen, and C3 levels.

Conclusions The knowledge-driven approach outperformed the data-driven approach which solely relied on feature selection methods. Our data suggests that the utilisation of five routine clinical parameters (proteinuria, albuminaemia, urea, C3) could be combined into accurate tool for predicting renal flares in SLE patients.

Conflicts of interest IP has received research funding and/or honoraria from Amgen, AstraZeneca, Aurinia, Bristol Myers Squibb, Elli Lilly, Gilead, GlaxoSmithKline, Janssen, Novartis, Otsuka, and Roche. The other authors declare that they have no conflicts of interest related to this work. The funders had no role in the design of the study, the analyses or interpretation of data, or the writing of the manuscript.

P63 TIME IS IMPORTANT: IMPLICATIONS OF DISEASE DURATION AND AGE FOR SYSTEMIC ERYTHEMATOSUS LUPUS NEUROIMAGING

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Objective Describe advanced and conventional Brain Magnetic Resonance Imaging (MRI) findings in Systemic Erythematosus Lupus (SLE) patients, that attended routine consultation, and identify possible factors associated.

Methods It was a cross-sectional study with forty-two SLE women (2019 EULAR/ACR criteria) that attended medical routine consultation. Brain MRI was performed on 1.5T system, including conventional sequences, diffusion tensor imaging (DTI), MR spectroscopy and MRI angiography without gadolinium (3D Time of Flight). The disease activity and cumulative organ damage were evaluated by SLEDAI and SLICC/ACR damage index. MRI dataset was blindly evaluated by two experienced radiologists. Statistical analysis was performed using JASP and Jamovi softwares.

Results Most of the patients did not have activity disease with neuropsychiatric alterations and have no irreversible organ damage, with SLEDAI less than 8 (70.73%) and SLICC = 0 (75.61%). White Matter Hypersignal Foci (WMHF) was the most frequent finding (61.9%), followed by brain atrophy (38.1%). Artery stenosis occurred in 14.29%, cerebral chronic

microbleeds in 14.29% and chronic lacunae infarct in 16.57%. NAA/Creatin ratio was lower in the group with brain atrophy and SLICC>0, denoting reduced neuronal population in this group. Findings of microstructural damage, such as low fractional anisotropy (FA) and high mean diffusibility (DM), were associated with brain atrophy, cerebral microbleed, reduced NAA/Creatin ratio, older age and disease duration.

Conclusions SLE is a possible risk factor for the development of micro and macrostructural brain damage. SLE patients could benefit from brain MRI in diagnosis and follow-up, even in remission or low disease activity. DTI can be used as predictor of cerebral damage, although prospective studies with larger cohorts are needed.

P64 EVALUATION OF CHANGES IN SLE PATIENTS' PHENOTYPE AT DISEASE ONSET, AND ASSESSMENT OF DISEASE ACTIVITY, DAMAGE AND THERAPY AT DIAGNOSIS AND DURING FOLLOW UP IN THE LAST FORTY YEARS: PRELIMINARY DATA OF A SINGLE CENTER EXPERIENCE

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Objectives Systemic lupus erythematosus (SLE) is associated with a high degree of variability at onset that can sometimes delay early diagnosis. Moreover, in the last decades, early diagnosis and therapeutic advances have led to better improved outcomes. The aim of this study was to evaluate the changes in the onset pattern of SLE and for changes in assessment and therapy at diagnosis and during the f-up.

Methods Medical records of 125 patients diagnosed between 1970 to 2019 and regularly followed up were reviewed. Patients were divided into 4 groups based on the year of diagnosis: 1970-'89, 1990-'99, 2000-'09, 2010-'19. Disease activity, cumulative organ damage and treatments were recorded at the time of diagnosis (T0) and at 1 (T1), 5 (T2) and 10 (T3) years after.

Results Our cohort consisted of 119 females and 6 males; as shown in figure 1 mean age of onset, and consequently mean age of diagnosis has significantly increased in different groups. A decreasing trend in the mean diagnostic delay was observed, although without statistical significance. Concerning the clinical presentation at onset, the most frequent symptoms observed were musculoskeletal (78,2%) and mucocutaneous (71%).

At the time of the diagnosis, no significant changes in disease activity or damage through the different decades (figure 2) were found. The only significant difference is the early use of HCQ: from less than 50% before 1999, to more than 70% of patients. During follow-up, a significant variation in disease activity in different decades appears at T2 and confirmed at T3, with a reduction in SLEDAI and a higher number of patients reaching low disease activity and remission. As

		Years of diagnosis				
	TOTAL (n=125)	'70-'89 (n=16)	'90-'99 (n=19)	2000-2009 (n=32)	2010-2020 (n=58)	p-value
Females, N (%)	119 (95,2)	15 (93,75)	18 (94,74)	32 (100)	54 (93,1)	0,5214
Males, N (%)	6 (4,8)	1 (6,25)	1 (5,26)	0 (0)	4 (6,9)	0,5214
Mean age of onset	30,62 (±12,91)	22,86 (±6,33)	26,42 (±10,29)	28 (±11,17)	35,59 (±14,11)	0,0011[1]
Mean age of diagnosis	31,95 (±12,95)	25,19 (±6,15)	28,47 (±10,27)	29,09 (±11,30)	36,53 (±14,47)	0,0050[2]
Mean diagnostic delay, months	15,83 (±32,54)	28,25 (±52,26)	24,21 (±48,13)	12 (±22,06)	11,6 (±18,89)	0,9164
		Clinical manifestations at onset				
	TOTAL (n=124)[3]	'70-'89 (n=16)	'90-'99 (n=18)[3]	2000-2009 (n=32)	2010-2020 (n=58)	p-value
Mucocutaneous, N (%)	88 (70,97)	14 (87,50)	15 (83,33)	21 (65,62)	38 (65,52)	0,1920
Musculoskeletal, N (%)	97 (78,23)	14 (87,50)	15 (83,33)	22 (68,75)	46 (79,31)	0,2540
Constitutional symptoms, N (%)	73 (58,87)	11 (68,75)	10 (55,55)	18 (56,25)	34 (58,62)	0,8449
Renal, N (%)	26 (20,97)	5 (31,25)	5 (26,32)	9 (28,12)	7 (12,07)	0,1521
Cardio-pulmonary, N (%)	8 (6,45)	0 (0)	1 (5,26)	2 (6,25)	5 (8,62)	0,6635
Neurological, N (%)	6 (4,84)	0 (0)	0 (0)	4 (12,50)	2 (3,45)	0,1091

[1] a significant difference was found among the groups. Comparing individual group each other there is a significant difference between "2010-2020" compared to all the other groups: 2010-2020 vs '70- '89 (p= 0.0006), 2010-2020 vs '90- '99 (p=0.0107), 2010-2020 vs 2000-2009 (p=0.0172).
[2]2010-2020 vs '70- '89 (p=0.0025), 2010-2020 vs '90- '99 (p=0.0277), 2010-2020 vs 2000-2009 (p=0.0137).
[3]missing onset data for 1 patient
Qualitative variables were compared with Chi-Squared or Fisher's exact test, quantitative variables with one-way Anova or Mann-Whitney test.

Abstract P64 Figure 1